REAL-TIME EXTRACTON OF READINESS-POTENTIALS FROM EEG

Kuniaki Uto, Keiichi Hibi and Yukio Kosugi
Interdisciplinary Graduate School of Science and Engineering, Tokyo Institute of Technology, Yokohama, Japan

Abstract-**Real-time EEG processing is desired as a communication tool for disabled individuals. However, motion-related potential as the cerebral phenomenon corresponding to the subject's intention for autokinesia is embedded in the background potential, therefore, the real-time extraction of significant signal is quite difficult.**

In this paper, our aim is a real-time readiness-potential extraction from EEG with relatively small number of scalp electrodes and the extraction of the difference among readiness-potentials based on different autokinesias by means of the combination of Independent component analysis (ICA) and scalp Laplacian.

Keywords - **Independent component analysis, readiness-potential, scalp Laplacian**

I. INTRODUCTION

For disabled individuals who suffered from postnatal disorder such as Amyotrophic Lateral Sclerosis (ALS), a way of communication, i.e. transmission of their emotion and intention, is strictly limited. Brain-computer interfaces (BCIs) are systems which analyze the electroencephalogram (EEG) of the patient in order to allow communication with the outer world. In this paper, we direct our attention to the extraction of the patient's intention to move the body.

The EEG of healthy body's movement has been observed in various researches and the averaging potential shows that the movement-related potential consists of the readiness-potential, pre-motion positivity and afferent potential. Although the movement-related potentials could correlate with the patient's intention, patients who suffer from ASL cannot move the muscles and consequently electromyography (EMG) and motor potential are hardly generated. ALS is a devastating neuromuscular disease that strikes adults in the prime of life. Fig.1 shows a rough sketch of the nervous system for movement control.

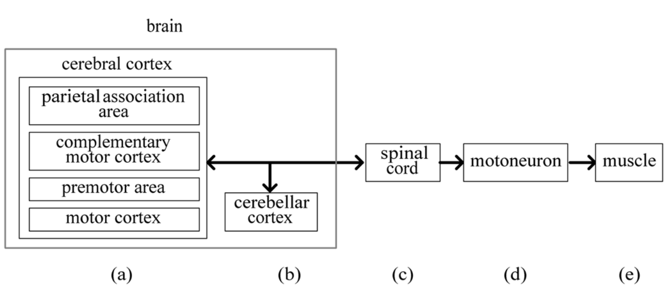

Fig. 1 Nervous system for movement control

Autokinesia originates from the intention for movement, i.e. movement order in the cerebral cortex and it interacts with some regions in the cerebellar cortex. The order for movement generated in the cerebral and cerebellar cortex is transmitted to motoneuron along the spinal cord and consequently the movement occurs and it stimulates motoneurons which control the movement of voluntary muscles. Therefore, if the suffered disease is a postnatal disorder in the motoneurons as well as ALS and the patient's motor cortex and other movement-related cortices are intact, the intention for movement is expected to generate significant activities in these cortices. Therefore, the readiness-potential which is originated in the cortical activities is a candidate for a probing signal which represents the patient's intention.

Dipole Tracing (DT) has given a great contribution to the comprehension of brain activities. A representative strategy for DT is a procedure of (1) modeling the conductive head model and (2) estimation of the positions and the amplitude of dipoles by solving the inverse problem based on the head model. We propose another way of an acquisition of movement-related potential as the dipole without the explicit usage of the head model [1]. We only use *a priori* information that each dipoles as cortical activities are independent and the EEGs are the linear transformation of the dipoles.

In this paper, we aim at the real-time extraction of the readiness-potential from EEGs and, furthermore, the extraction of the difference among readiness-potentials based on different autokinesias, e.g. appendicular information separation.

II. METHODOLOGY

Unfortunately, human thinking process, i.e. the brain activity, is quite complicated in comparison with that of other creatures. Therefore, the evoked and movement-related cortical potentials are embedded in the spontaneous potentials originated in various brain activities, so that the extraction of these potentials is extremely difficult.

A Averaging method

Averaging method has been mostly used as a standard way of the repetitive signal extraction. It has clarified that the movement-related cortical potentials are observed as a compound of readiness-potential, pre-motion positivity, motor potential and afferent potential. In case of seeking the readiness-potentials, reverse averaging on the basis of EMG trigger is a common method.

Report Documentation Page

Report Date	Report Type	Dates Covered (from... to)
25 Oct 2001	N/A	-

Title and Subtitle Real-Time Extraction of Readiness-Potentials From EEG	**Contract Number**
	Grant Number
	Program Element Number
Author(s)	**Project Number**
	Task Number
	Work Unit Number
Performing Organization Name(s) and Address(es) Interdisciplinary Graduate School of Science and Engineering Tokyo Institute of Technology Yokohama, Japan	**Performing Organization Report Number**
Sponsoring/Monitoring Agency Name(s) and Address(es) US Army Research, Development & Standardization Group PSC 802 Box 15 FPO AE 09499-1500	**Sponsor/Monitor's Acronym(s)**
	Sponsor/Monitor's Report Number(s)
Distribution/Availability Statement Approved for public release, distribution unlimited	
Supplementary Notes Papers from 23rd Annual International Conference of the IEEE Engineering in Medicine and Biology Society, October 25-28, 2001, held in Istanbul, Turkey. See also ADM001351 for entire conference on cd-rom., The original document contains color images.	
Abstract	
Subject Terms	
Report Classification unclassified	**Classification of this page** unclassified
Classification of Abstract unclassified	**Limitation of Abstract** UU
Number of Pages 4	

Averaging method relies on an assumption that all the background potentials are independent from the evoked potentials and independent identically distributed (i.i.d.) so that those background potentials, e.g. spontaneous Alpha rhythms, are cancelled out according to the law of large number.

The background potential is originated in various cortical activities, so that it is quite difficult to verify the validity of the assumption but the experimental results have been given a lot of significant information related to the cortical activities. For instance, in case of right finger movement, a remarkable potential which corresponds to movement-related potential appears around F3 (International 10-20 system) and it reflects the cortical activity in the motor area of the left frontal lobe.

Thus, averaging method is simple but it gives very effective information. However, it is far from real-time processing; therefore, averaging method is out of touch with reality as an interface for disabled individuals which requires a real-time perception of meaningful potential.

B Independent component analysis (ICA)

EEG is a potential on the scalp and it is a reflection of electrical activities in the cortices. Moreover, the electrical activities originate in the depolarizations of enormous number of neurons. Therefore, it is not realistic to detect all the neuronal activities. Specific functions of information processing in the brain strongly correlate with specific regions in the brain. For instance, visual areas for visual processing are bound in some regions in the occipital lobe. Motion-related regions, i.e. motor cortex etc., are found in some regions in the frontal lobe. When a group of active neuron is localized on a small region of the cortex, the group is approximated as a single-dipole.

The DT based on the conductor head model is derived from the Maxwell's equations and it indicates the linear correlation between the dipoles and the scalp potentials. When **U** represents a vector whose elements denote signals observed by scalp electrodes and **V** represents a vector whose elements denote localized cortical activities, the scalp electrical signal vector **U** is given by the product of a linear matrix **A** and the cortical activity vector.

$$\mathbf{U} = \mathbf{AV} \tag{1}$$

Here, on the basis of the above facts, we assume that (1) principal movement-related cortical potentials are localized on fixed locations and independent to each other and (2) each observed EEG is regarded as a linear combination of those independent dipoles and background potential. Independent component analysis (ICA) [2] aims at finding a linear representation of non-Gaussian data so that the components are statistically independent. ICA has given some successes in artifact indentifications and cortical activity extractions [3],[4],[5].

For n observed time series data $x_i(t)$ which are linear mixtures of independent sources $s_j(t)$, we drop the time index t and give $\boldsymbol{x}$, $\boldsymbol{s}$ as the n dimensional vectors with components $x_i(t)$ and $s_i(t)$, i=1,…,n respectively. We look upon each **x** and **s** as samples of random vector. Then, for given mixing matrix **A**, the mixing model is written as

$$\mathbf{x} = \mathbf{As}. \tag{2}$$

Our goal is finding **W** as an inverse of **A** and acquiring **s** as

$$\mathbf{s} = \mathbf{Wx}. \tag{3}$$

The independency of **s** is equivalent to non-Gaussianiety of **s**, therefore, now our aim is transformed to the search for **W** which leads the linear mixing vector **y** to have maximum measure of non-Gaussianiety.

$$\mathbf{y} = \mathbf{Wx} \tag{4}$$

Non-Gaussianiety is evaluated by measurements such as Kurtosis, Negentropy, mutual information. In this paper, we applied the FastICA [6].

C Scalp Laplacian

Scalp potential generated by cortical activities has low spatial resolution because of low conductivity of the skull etc. Body-surface Laplacian is used for the enhancement of spatial resolution of the scalp potentials and it gives better reconstruction of cortical potentials in comparison with the case of the reconstruction based on the scalp potentials [1],[7]. The Laplacian EEG is proportional to the second spatial derivative of the electrical potential on the surface, and can be interpreted as an equivalent charge or the derivative of the normal component of the current density on the body surface. In our research, we derive the Laplacian EEG by numerical analysis based on scalp potentials on International 10-20 system.

D Our method

As mentioned in the above, our aim is the readiness-potential detection. We use (1) ICA and (2) scalp Laplacians and ICA for the processing of acquired EEGs.

ICA cannot identify the particular order of the independent components, i.e. localized cortical activities. Therefore, even if we can extract a significant signal for detecting a readiness-potential to a certain observed EEG, it does not give information such as which independent component denotes the readiness-potential for other observed EEGs. We assume that whenever the subject intends to move a specific part of his body, the cortical activity related to the readiness-potential occurs in exactly the same part of the brain cortex and, furthermore, the mixing transformation is invariable. Then, if we can acquire an appropriate independent components and accordingly an appropriate mixing matrix, the mixing matrix could be used to other observed EEGs. Thus, the significant signals, i.e. the cortical activities related to the readiness-potentials, are expected to appear in the same order.

For each EEG segments, e.g. $\mathbf{e_1}$ and $\mathbf{e_2}$, if the segments are independent to each other, each ICA processing of these segments is expected to produce uncorrelated independent component $\{s_i^1\}_{i\in n}$ and $\{s_i^2\}_{i\in n}$ and similarly the mixing matrices $\mathbf{A}_1$ and $\mathbf{A}_2$ is expected to be uncorrelated. n is the number of independent source. Our assumption is that $\mathbf{A}_1$ and

$\mathbf{A}_2$ are equivalent so that if we derive $\mathbf{A}_1$ on the basis of $\mathbf{e}_1$, it can be applied to $\mathbf{e}_2$ and the order of obtained independent sources $\{s_i^2\}_{i\in n}$ are same as $\{s_i^1\}_{i\in n}$.

III. Experiment

A Experimental setup

EEG acquisition system:

The EEG acquisition system used in our research is depicted in Fig.2.

The EEGs were recorded with scalp electrodes (a) attached to the scalp and positioned at C3, C4, Cz, F3, F4, P3, P4, T3 and T4 (International 10-20 system). Recording were carried out with a Digital Bio-Amplifier 5200 (NF Electronic Corp.), consisting of a EEG Headbox 5202 (14 EEG channels, sensitivity: 409.6μVpp/FS, 2 EMG channels, sensitivity: 10.24mVpp/FS, time constant: 0.3s) and a Processor Box 5201 (IIR digital filtering, decimation). In the headbox (b), filters with 1.6Hz-50Hz bandwidth are inserted and the sampled at the rate of 1kHz. Processor box (c) collects the digital signal from the headbox. Then, the EEG is processed by a PC (d) (Pentium III 550MHz processor, 392Mbytes memory).

All measurements were carried out inside a shield room (Nihon Itagarasu Kankyo Ameniti NEA Corp., model “Mag Savor 15”) ensuring 60dB attenuation for electric waves (0.2~18MHz) and of 40dB for magnetic waves (0.2~1.9MHz).

Subject:

A healthy male volunteer aged 25 was a subject for this experiment.

Experimental task and the recording:

Four movements corresponding to movements of subject’s extremities, i.e. computer mouse clicks as grip movement of both hands and stepping of electrical button as step movements of feet, are selected as the experimental task. Each movement is repeated 100 times successively.

B EEG processing and data analysis

Starting trigger of each movement is marked as the electrical signal by a click or stepping. Each EEG segment of a period between 0.75s before the trigger and 0.25 after the trigger, i.e. the period which conspicuously characteristic feature is observed in averaging method, is used for the EEGs processing. The number of segments for each movement is 100 respectively.

Each EEG segment was processed by (1) averaging method, (2) ICA and (3) scalp Laplacians + ICA.

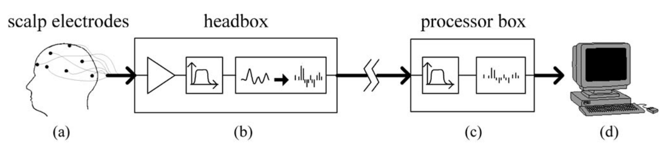

Fig. 2 EEG acquisition system

IV. Results

Fig.3 shows a 9-channel set of EEG recordings of right hand grip movement.

Fig.4 shows the independent source estimates by means of ICA of the EEGs of Fig.3. It is hard to pick up the characteristic features of the movement-related source signals.

Fig.5 shows the independent source estimates by means of ICA of five EEG (Fig.3) Laplacians with two neighborhoods, i.e. C3 with the neighborhoods T3, Cz, C3 with F3, P3, C4 with T4, Cz, C4 with F4, P4, and Cz with C3, C4. In Fig.5, the second signal seems to represent the characteristic feature of readiness-potential.

Fig.6 shows the independent source estimated by means of ICA of two EEG (Fig.3) Laplacians with four neighborhoods, i.e. C3 with the neighborhoods T3, Cz, F3, P3, and C4 with the neighborhoods T4, Cz, F4, P4. In Fig.6, the second signal has a quite similar feature to that of the readiness-potential, i.e. slow negative potential, in spite of the expectation that the dimension of the EEGs, i.e. two channels, is too simple to deal with the scalp potential and the extracted signals are unreliable. The arrangement of the scalp Laplacians mignt have a good effect on the result, because the movement of one side of the body is expected to cause a conspicuous difference in both cortical activities.

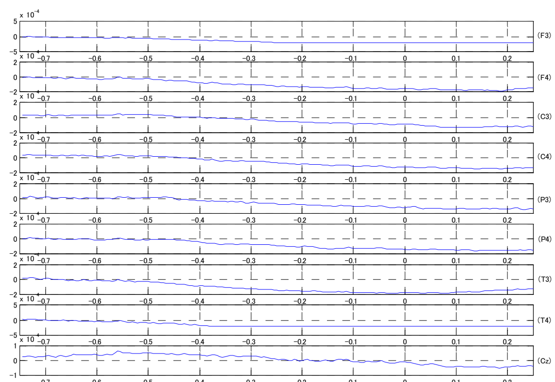

Fig. 3 9-channel set of EEG.

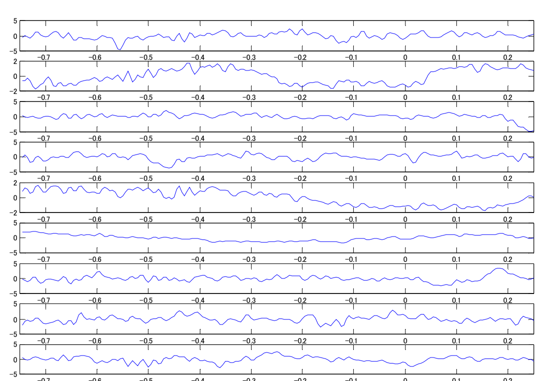

Fig. 4 ICA of EEGs of Fig.3.

We applied the inverse matrix generated in ICA of Fig.6 to another EEG segment related to the same autokinesia as Fig.6, i.e. right hand grip movement, to evaluate the robustness of the acquired inverse matrix. Fig.7 shows the linearly transformed signals. These signals are similar in features to the signals in Fig.6, i.e. the readiness-potential appears in the second signal. This result indicates the robustness of the order of the independent components derived by the inverse matrix, and consequently the robustness of the matrix.

V. Discussion

Although we found some features related to readiness-related potential, we cannot find definite characteristic features among different types of autokinesias. Therefore, we need more experiments with more electrodes for the extraction of distinct differences in readiness-potentials among different types of autokinesias.

In this paper, we proposed the fixed matrix method in which a fixed matrix generated by a EEG is used as a universal matrix. This method is proposed on the basis of an assumption that the mixing matrix is fixed at least when the type of autokinesias is same. However, the different type of the autokinesia is expected to evoke the cortical activity in the different region on the cortex. Therefore, for a motion detection, we have to (1) prepare a set of universal matrices and the template signals which correspond to each types of autokinesia respectively and (2) adopt the best matching template and the equivalent type of as the estimated movement.

VI. Conclusion

In this paper, we proposed a readiness-potential extraction method based on the compound of ICA and scalp Laplacians. The experiments showed some significant signal extractions from the EEGs which gave the promising expectation for real-time extraction of readiness-potential from the EEGs.

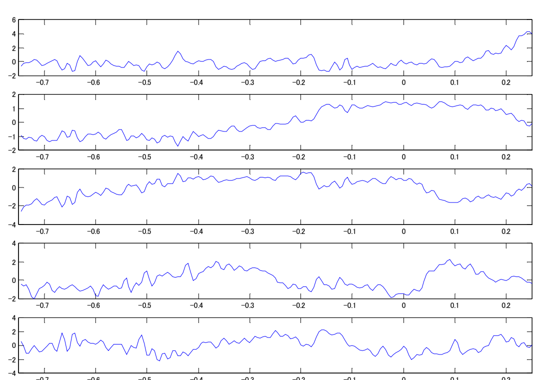

Fig. 5 ICA of five EEG Laplacians.

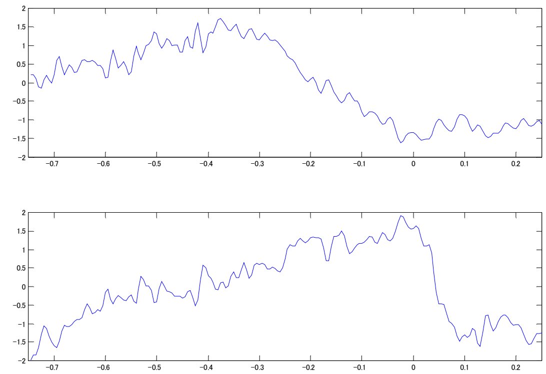

Fig. 6 ICA of two EEG Laplacians.

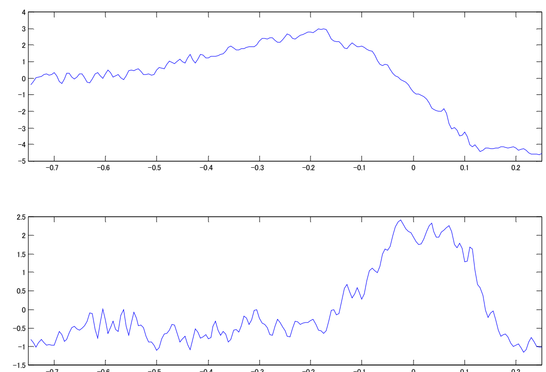

Fig. 7 Linearly transformed signals.

References

[1] B. He, “High-resolution source imaging of brain electrical activity,” *IEEE eng. med. biol. mag.*, vol.17, no.5, pp.123-129, 1998.

[2] A. Hyvärinen, E. Oja, “Independent component analysis : algorithms and applications,” *Neural Networks*, vol.13, no.4-5, pp.411-430, 2000.

[3] R. Vigário, “Extraction of ocular artifacts form EEG using independent component analysis,” *Electroecceph. Clin. Neurophysiol.*, vol.103, pp.395-404, 1997.

[4] R. Vigário, J. Särelä, V. Jousmäki, M. Hämäläinen, E. Oja, “Independent component approach to the analysis of EEG and MEG recordings,” *IEEE trans. biomed. eng.*, vol.47, no.5, pp.589-593, 2000.

[5] S. Makeig, T. P. Jung, A. Bell, D. Ghahremani, T. Sejnowski, “Blind separation of auditory event-related brain responses into independent components,” *Proc. Nat. Acad. Sci. USA*, vol.94, pp.10979-10984, 1997.

[6] A. Hyvärinen, E. Oja, “A fast fixed-point algorithm for independent component analysis,” *Neural Computation*, vol.9, pp.1483-1492, 1997.

[7] B. He, D. Wu “A bioelectric inverse imaging technique based on surface Laplacians,” *IEEE trans. biomed. eng.*, vol.44, no.7, pp.529-538, 1997.